Comparison of Large Aperture Scintillometer and Satellite-based Energy Balance Models in Sensible Heat Flux and Crop Evapotranspiration Determination

Mcebisi Mkhwanazi[1], José L. Chávez[2], Evan H. Rambikur[3]

Civil and Environmental Engineering Department

Colorado State University

Fort Collins, Colorado, U.S.A.

jose.chavez@colostate.edu

Abstract-**The estimation of crop water use or evapotranspiration (ET) is an important aspect of water management especially in arid and semi-arid regions. Various methods have been used in the estimation of ET including remote sensing (RS) based models, and these have an added advantage of estimating ET over a large area (e.g., regionally). This study looked at two models of estimating ET; Mapping evapotranspiration at high Resolution with Internalized Calibration (METRIC) and the Surface Energy Balance Algorithm for Land (SEBAL). Satellite images from Landsat 5 for 2010 for two alfalfa fields in Rocky Ford, Colorado, were processed and analyzed to obtain sensible heat flux (H). Both RS models employ the energy balance (EB) method and estimate net radiation (R_n) and soil heat flux (G) similarly. However they differ in the approach to calculate H. Since ET is determined as a residual in the EB equation, the accurate estimation of H becomes critical. The objective of the study was to assess the RS estimates of H with H measured using a Large Aperture Scintillometer (LAS). Further comparison was done for ET. Results indicated that METRIC more accurately estimated H and ET than SEBAL. For hourly ET, SEBAL showed a relative error up to 38% while METRIC resulted in a relative error up to 11%. Both models reported larger errors for dry fields depicting smaller fractional vegetation cover values. The results of this study indicate that there is an opportunity to improve the RS methods discussed by incorporating surface heterogeneity and perhaps the correction of radiometric surface temperature for atmospheric effects.**

Keywords-Spatial Evapotranspiration; METRIC; SEBAL; Satellite Multispectral Imagery; Surface Energy Balance; Scintillometry

I. INTRODUCTION

Irrigation water for crops is the major consumptive use of water resources globally. Recently there has been an increasing competition for water from agriculture, urban use, industry, recreation, and livestock watering. The phenomenon of a changing climate is set to exacerbate an already serious situation. Studies in research literature show how agricultural production, especially in arid and semi-arid regions, will be one of the sectors most vulnerable to climate change and variability (Challinor et al., 2005). Spatial and temporal changes in precipitation and temperature patterns will have an impact on the viability of dry land farming and therefore necessitate irrigation where rainfall was previously adequate. Areas which are already under irrigation will demand more water due to the increased temperatures (Knox et al., 2010). Due to the above mentioned challenges, it is important that the management of agricultural water be improved, which would

involve the accurate estimation of consumptive use otherwise known as evapotranspiration. Evapotranspiration (ET) is an essential component of the water balance and it is a significant consumptive use of precipitation and water applied for irrigation on cropland (Paul et al., 2011). Several methods are being used to measure and estimate ET, one of them being the lysimeter method. This method may be accurate but lysimeters are expensive and the extent of their measurement is localized (i.e., they provide data for a small area, so can only be used in field locations), Elhaddad and Garcia (2008).

Another widely used method of modeling ET is the reference evapotranspiration and crop coefficients methods. This method basically is a 3-step approach. The first step is the computation of reference ET for a reference crop which is either alfalfa (ET_r) or clipped grass (ET_o), and using local weather data (ASCE-EWRI, 2005). These are then converted to crop ET by using crop-coefficients (K_c) which are for a specific crop, and also depend on the reference crop type used; whether they are ET_o based or ET_r based. The reference ET – K_c method assumes an ideal situation whereby there is no crop stress, and the crop is transpiring at its potential. However this is generally not the case, so a third step would include a soil water content reduction term that would reduce the K_c value.

Other methods such as the Bowen ratio (BR) surface energy method and the eddy covariance are also used. The Bowen ratio depends on sensor accuracy to measure small differences in air temperature and humidity between two levels above the surface of interest (Bastiaanssen et al., 2005). There are also assumptions employed for the BR method (e.g., that the turbulent transfer coefficients for heat and vapor are identical, and also that there are no horizontal gradients of temperature and humidity; the latter assumption would require an adequate fetch). The eddy covariance method usually does not close the energy balance (EB) (Twine et al., 2000) because it tends to under-sample the different eddies (large or small) that carry heat and water vapor. The lack of EB closure, by the EC system, results in inaccurate estimations of sensible heat and latent heat fluxes. The lysimeter although often regarded as more accurate would still depend on the installation, calibration, and maintenance for accuracy. The surface conditions inside a lysimeter box should be representative of the conditions surrounding it (i.e., the vegetation and soil water content status in the lysimeter should be similar to the surrounding area or extended field area). Most of these

methods just discussed are appropriate for field estimation of ET and would be expensive for regional coverage.

Remote sensing (RS) is an indirect method for estimating the energy balance components and ET. This technique makes use of the land surface energy balance equation (1).

$$R_n = LE + G + H \qquad (1)$$

where R_n is net radiation, LE is latent heat flux, G is soil heat flux and H is sensible heat flux (all in units of W m^{-2}).

In this technique satellite sensed radiances from the earth surface are converted into surface properties such as albedo, leaf area index, vegetation indices, surface emissivity, and surface temperature. These variables and parameters are used to estimate the various components of the energy balance model (i.e., R_n, H, G then LE as a residual), Gowda et al. (2011).

Several models have been developed to spatially estimate ET. Among them are the Surface energy balance algorithm for land (SEBAL; Bastiaansen et al., 1998), the Mapping Evapotranspiration with Internalized Calibration (METRIC; Allen et al., 2007) model, the Remote Sensing of Evapotranspiration (ReSET; Elhadad and Garcia, 2010) method, and the Analytical Land Atmosphere Radiometer Model (ALARM; Suleiman et al., 2009). SEBAL was developed to estimate ET over large areas using satellite surface energy fluxes (Bastiaanssen et al., 1998). SEBAL is said to be capable of estimating ET without prior knowledge on the soil, crop, and management conditions (Bastiaanssen et al., 2005). This method has been used widely including locations in the U.S.A., Africa, Europe and other parts of the world. METRIC, on the other hand, is a modification of SEBAL and is based on a similar principle (to estimate H), making use of the near surface temperature gradient (dT) function as proposed by Bastiaanssen (Singh et al., 2008). Another method, the Surface Aerodynamic Temperature (SAT), models the aerodynamic surface temperature (T_o), a parameter which is not measured and not easily estimated, to determine H. Other methods often use radiometric surface temperature (T_s) in the place of T_o, which may result in the overestimation of H and thus underestimation of ET (Chávez et al., 2010). The ReSET model does not assume that weather parameters from one weather station will be applicable for the whole area represented in an image which can be very large (e.g., 185 x 172 km for Landsat 5 images). This method takes into consideration the spatial variability, and interpolates between available weather stations in time and space (Elhaddad and Garcia, 2008). The use of satellite based energy balance models has some advantages over the other traditional methods. One is that it provides regional estimates rather than field estimates of ET. Another advantage is that remote-sensing methods estimate the actual evapotranspiration, while some other methods use meteorological data to estimate reference ET to subsequently estimate actual ET using crop coefficients.

Remote sensing methods do however require some ground truth data to measure their performance (Hoedjes et al., 2007).

In this study, the scintillometry technique is used as an independent reference to evaluate the performance of the remote sensing energy balance methods. This method uses properties of the near-surface atmosphere (surface layer) to solve for sensible heat flux (H) and surface energy balance (Eq. 1) to further solve for ET. The advantage of using the LAS to

evaluate RS-EB flux estimates is that the LAS measurement represents a relatively large spatial area which is more consistent with the spatial scale of the RS pixel sizes than other methods such as lysimetry or eddy covariance (Brunsell et al. 2011). Over heterogeneous terrain, where there may be spatial variability in the surface ET, comparison of LAS- and RS-derived ET fluxes is performed by computing the spatially distributed weighted contribution percentages to the LAS H measurement within the surface heat source area (Hoedjes et. al., 2007).

The objective of this study was to compare two remote sensing based energy balance models (i.e., SEBAL and METRIC) with a Large Aperture Scintillometer (LAS). The study compared the sensible heat flux and the hourly crop evapotranspiration for the 2010 alfalfa growing season in Eastern Colorado, U.S.A. Studies have shown the challenges in accurately estimating H, which thus result in further inaccuracies in the estimation of ET (Singh et al., 2008; Gowda et al., 2008). Various satellite-based energy balance models employ different approaches in the estimation of H. The aim therefore was to determine how accurately these models estimate H and how such estimation of H affects the accuracy of ET estimation.

II. MATERIALS AND METHODS

A. Study Area

This study was carried out at the Colorado State University (CSU) Arkansas Valley Research Center (AVRC) near Rocky Ford, Colorado (U.S.A.) with geographic coordinates being 38°02'N, 103°41'W, and the area's elevation 1274 m above sea level. Two fields were selected for the study, both equipped with a Large Aperture Scintillometer system, from Kipp and Zonen[1], and both under alfalfa (Figure 1). The transmitter and receiver of the LAS system were installed at opposite edges of the field, and the electromagnetic radiation was transmitted across the field. The alfalfa was irrigated with a furrow irrigation system using siphons and a head ditch. As part of the instrumentation in the field, there were four net radiometers, including two Q7.1 net radiometers (REBS, CSI, Logan, Utah, U.S.A.), one at each lysimeter, one CNR1 4-way, net radiometer (Kipp and Zonen, Bohemia, New York, U.S.A.) near the LAS 1 receiver and one NR-Lite net radiometer (Kipp and Zonen, Bohemia, New York, U.S.A.) near the LAS 2 receiver. In addition, there were two infra-red thermometers (IRT, Apogee model SI-111, CSI, Logan, Utah, U.S.A.) to measure the crop radiometric surface temperature. Soil heat flux plates (REBS model HFT3, CSI, Logan, Utah, U.S.A.) were buried in the ground at locations proximal to the above described measurements of net radiation, with depths ranging from 8 to 15 cm, along with soil temperature and soil water content sensors, for the estimation of soil heat flux at the ground surface.

B. Landsat Satellite Datasets and Processing

Landsat 5 Thematic Mapper cloud free satellite images (Path 32, Row 34), were obtained from the United States Geological Survey (USGS) Earth Explorer site [(http://edcsns17.cr.usgs.gov/NewEarthExplorer/)] for the 2010 growing season. The acquisition dates were July 9, August 10, August 26, September 11 and October 13 for the location of

LAS 1. For LAS 2 location only images for dates September 11 and October 13 were acquired as the LAS was installed late in the season and only images for the two dates were cloud free and thus usable after the installation. The time of overpass of the satellite ranged from 10:22 – 10:24 a.m., local standard time. The images were processed using the Erdas Imagine 2010 software (ERDAS, Norcross, Georgia, U.S.A.).

C. Remote Sensing Based Algorithms

SEBAL and METRIC both estimate ET through the land surface energy balance (EB) method, using remotely sensed surface reflectance in the visible and near infra-red portions of the electromagnetic spectrum. The radiometric surface temperature was also measured using the satellite infra-red thermal band. The approach was to convert satellite sensed radiances into land surface characteristics that will include surface albedo, leaf area index, vegetation indices, surface emissivity, and surface temperature. These parameters and variables were used to calculate the various components of the energy balance (R_n, G, and H) then LE estimated as residual of the land surface balance as given in equation (1).

These two RS methods do not differ much in the estimation of R_n and G. However they do use different approaches in the estimation of H. As has been mentioned earlier, it is difficult to accurately estimate H. This paper will focus on the differences in the approaches to determine H, and how that further affects the estimation of ET.
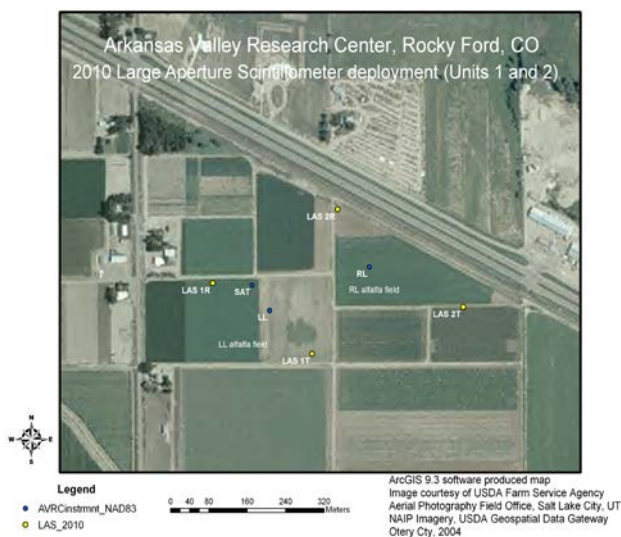

Figure 1 Aerial image showing the two scintillometer deployments (LAS) along with additional (ancillary) research instrumentation

D. Sensible Heat Flux (H) Estimation

The basic calculation of H is performed by using the bulk aerodynamic method as shown in equation (2) below.

$$H = \rho_a C_{pa} (T_o - T_a)/r_{ah} \qquad (2)$$

where ρ_a is the air density of moist air (kg/m^3), C_{pa} is specific heat of dry air (~1004 J/kg/K); T_a is average air temperature (K) at screen height (typically at 2 m), T_o is the average surface aerodynamic temperature (K). T_o is not measured and may be difficult to estimate, thus some users substitute radiometric surface temperature (T_s) for T_o. However, the assumption that aerodynamic temperature is equivalent to the radiometric surface temperature may result in errors in the estimation of H. This is because there may be differences between T_o and T_s especially over heterogeneous surfaces and dry surface conditions and/or over sparse

canopies. In SEBAL and METRIC, that challenge is said to be overcome by introducing a dT function which replaces ($T_o – T_a$) in equation (2). The term dT is the temperature difference at two levels at near surface, and the levels are 2m and 0.1m.

In the process of determining the dT function two extreme pixels, a wet and dry pixel, are selected. In the selection of a wet pixel, it would be a pixel that would have a low temperature; with the assumption that the low temperature is so because the available energy (R_n – G) is only used to evaporate water and not to warm the surface. Therefore SEBAL assumes that at the wet/cold pixel H equals zero. Traditionally in SEBAL a water body would be selected, however the later recommendation was that a wet agricultural field be selected, so that the aerodynamics would be similar to that of other vegetative surfaces. Therefore, dT in the wet pixel is assumed to be zero. This is a reasonable assumption, except in regions of extreme aridity where there would be regional advection of sensible heat energy into the irrigated projects which cause the available energy to exceed R_n – G, hence negative values of H. METRIC differs from SEBAL in the selection of the wet pixel and the assumptions associated with it. For the wet pixel, a well vegetated pixel having relatively cool temperature is selected. However instead of assuming a zero value for dT_{cold} for that pixel, dT_{cold} is given as:

$$dT_{cold} = (R_n - G - 1.05\, \lambda ET_r)\, r_{ah} / \rho_a C_p \qquad (3)$$

ET_r is the hourly reference ET computed from an alfalfa reference using weather data from the area of study, and r_{ah} is the surface aerodynamic resistance (s m^{-1}), and λ is the latent heat of vaporization (J/kg) to convert ET_r (mm h^{-1}) to latent heat flux (W m^{-2}). The standardized ASCE EWRI Penman-Monteith equation for alfalfa reference (ASCE-EWRI, 2005) was used for the calculation of ET_r. The ET_r is multiplied by 1.05 assuming that a pixel selected would be an area with large vegetation biomass and will have a larger surface wetness and therefore should have ET that is about 5% greater than ET_r (Allen et al., 2005).

To select a dry pixel, a pixel with a high temperature would be a candidate since it would indicate dryness. In addition, the pixel should have small biomass or leaf area index value or depict a larger albedo. However, care should be taken that man-made surfaces such as highways are not selected. A dry agricultural area (possibly fallow) or bare soil would be recommended. This pixel is assumed to have ET of zero, and a large value of dT. METRIC would also assume the same as with SEBAL, except that METRIC would consider the possibility of the hot pixel not having LE that equals zero, and therefore in METRIC, a daily surface soil water balance is run for the hot pixel to confirm that ET equals zero or to supply a nonzero value for ET for the hot pixel if a recent wetting event has occurred in the selected extreme pixel area. Once the dry/hot pixel is identified, the value of H can be calculated using R_n and G from the image for the pixel. The dT value can then be calculated using equation (4).

$$dT_{hot} = H \times r_{ah}/(\rho_a \times C_{pa}) \qquad (4)$$

SEBAL and METRIC assume a linear relation of dT to radiometric surface temperature and the relationship is explained by the use of coefficients a and b whereby:

$$dT = aT_s + b \qquad (5)$$

where the coefficients a and b can be found as follows:

$$a = \frac{dT_{hot} - dT_{cold}}{T_{s_{hot}} - T_{s_{cold}}} \quad b = dT_{hot} - a \times T_{s_{hot}}$$

E. Sensible Heat Flux Measurement Using Large Aperture Scintillometer

A scintillometer measures the fluctuation of a light beam intensity after being propagated through a turbulent medium (Chehbouni et al., 1999). The large aperture scintillometer consists of a transmitter and a receiver. The transmitter emits electromagnetic radiation over a distance referred to as the path length. The distance ranges from several hundreds of meters up to 10 km (Hoedjes et al., 2007). The electromagnetic radiation emitted is scattered by turbulence in the lower atmosphere, and what is measured at the receiver is then used to interpret the conditions along the path. Specifically, the LAS measures the log variance of the beam intensity at the receiver, which is related to the change in the refractive index of air (C_n^2, $m^{-2/3}$). The C_n^2 parameter can be further related to the sensible heat flux (H, Wm^{-2}) with input of additional variables including the Bowen Ratio, and by employing the Monin-Obukhov Similarity Theory for a thermally stratified surface layer. For a comprehensive discussion on the theory and equations supporting the use of the LAS, the reader is referred to Moene et al. (2005). Since the primary output of the LAS is H, further measurement of R_n and G variables are necessary to compute ET by energy balance. Caution must be exercised here to ensure that the R_n and G measurements are representative of the area sampled by the LAS. Validation of remote sensing models like SEBAL and METRIC using a scintillometer is preferred over other ground-truth methods like lysimetric ET measurement because the pathlength of LAS is comparable to the spatial resolution of satellite images (30-1000 m) (Brunsell et al., 2011). The H measurements taken using the LAS were acquired in 15 minutes intervals. For comparison purposes, the 10:30 reading which would be an average between 10:15 and 10:30 a.m. was used since the satellite overpass time was averaged at 10:23 am.

III. EVALUATION CRITERION

Several performance indicators are used to evaluate the model performance in estimating H and ET and are defined as follows:

Coefficient of determination (R^2): This is a measure of the proportion of variance in measured data that is explained by a model. It allows one to determine the certainty of making a prediction from a model. It ranges between 0 and 1, with a value of 1 being the optimal. Typically, values that are greater than 0.5 are considered as acceptable.

$$R^2 = \frac{\left(\sum_i^n (O_i - \bar{O})(M_i - \bar{M})\right)^2}{\sum_i^n (O_i - \bar{O})^2 \times \sum_i^n (M_i - \bar{M})^2} \quad (6)$$

where, O is the observed (measured) value and M is the predicted or derived (remote sensing based in our case) value. The bars above the variables denote averages.

Mean Bias Error (MBE): This indicator is usually used to determine the average model bias or average over- or under-prediction. MBE is obtained by summing up the differences between predicted and observed values. Positive values indicate model over-estimation bias, and negative values indicate model under-estimation bias (Willmott 1982; Katiyar

et al., 2010), and zero is interpreted as absence of bias and not necessarily absence of error.

$$MBE = \frac{1}{n} \sum_i^n (M_i - O_i) \quad (7)$$

Root Mean Square Error (RMSE): This is a commonly used error index statistic. A smaller RMSE value indicates a smaller error spread and variance and therefore a better model performance. It measures the magnitude of the spread of errors, squaring errors before averaging them. Therefore, the RMSE gives a relatively high weight to large errors. Willmott (1982) defines RMSE as:

$$RMSE = \sqrt{\frac{1}{n} \sum_i^n (M_i - O_i)^2} \quad (8)$$

Nash-Sutcliffe Coefficient of Efficiency (NSCE): This is usually used to assess the predictive ability of a model. To determine NSCE, the sum of absolute squared differences between the predicted and observed values, normalized by the variance of the observed values is subtracted from one. NSCE values range between $-\infty$ and 1. The closer the model efficiency is to 1, the more accurate the model is, with values above zero indicating an acceptable performance level, while values less than zero indicate unacceptable performance (Paul et al., 2011).

$$NSCE = \frac{\sum_i^n (O_i - \bar{O})^2 - \sum_i^n (M_i - O_i)^2}{\sum_i^n (O_i - \bar{O})^2} \quad (9)$$

where, M is the model estimation or prediction for H or ET, either for SEBAL or METRIC models. O is the measured or observed H or ET using a large aperture scintillometer (LAS). n is the number of observations and i is the specific observation.

IV. RESULTS AND DISCUSSION

The sensible heat fluxes obtained from SEBAL and METRIC were compared with those measured using the Large Aperture Scintillometer (LAS). In addition, the ET estimated from the models and that from LAS were compared. For SEBAL, there was a large positive Mean Bias Error for H estimation of 31.79 Wm^{-2} (36.7%) and RMSE of 59.6 Wm^{-2} (68.9%), which indicated an overestimation (Figure 2). Both SEBAL and METRIC seemed to consistently overestimate sensible heat flux, as shown in Figure 2 (SEBAL) and Figure 3 (METRIC) where most of the points are above the 1:1 line. The NSCE for SEBAL was -0.13, indicating that the model performance was unacceptable, as it is only acceptable when it has values between 0 and 1. METRIC, for the estimation of H, showed a positive MBE of 34.08 Wm^{-2} (39.4%) and RMSE of 28.9 Wm^{-2} (33.4%). The R^2 of 0.86 indicated less error variance, and the NSCE of 0.48 was within the acceptable range of model performance.

The SEBAL estimated H ranged, for the remote sensing scene, from 18 to 250 Wm^{-2}, with a standard deviation of 110 Wm^{-2}. The METRIC estimated H ranged from 6 to 217 Wm^{-2} with a standard deviation of 76 Wm^{-2} while the LAS measured H ranged from 11 to 170 Wm^{-2}, with a standard deviation of 65 Wm^{-2}. There seems to be more discrepancy between estimated and measured H for larger values of H, and this is usually associated with conditions of dry and heterogeneous surfaces. Chávez et al. (2009a) found out that METRIC results improved if atmospheric effects on the radiometric surface temperature were accounted for (correction) using a radiative transfer model (MODTRAN), and when a local calibration for the leaf area index sub-model was incorporated in the

algorithm. Therefore, the estimation of H may have been affected by the lack of an absolute radiometric calibration of the thermal imagery accounting for atmospheric effects (optical thickness) and perhaps due to surface heterogeneities (which affect the roughness length for momentum and heat transfer). For example, in the case of August 26, where the alfalfa had just been harvested and bare patches were observed, and there had been no irrigation for 4 weeks, SEBAL and METRIC overestimated by 88 and 57 Wm^{-2}, respectively. Singh et al. (2008) made a similar observation with SEBAL underestimating H by 50%, obtaining an RMSE of 108 Wm^{-2} and an R^2 of 0.232. In that study, it was mentioned that most of the underestimations occurred when the crop had reached physiological maturity and most of the available energy was used for warming the microclimate than being used for ET. Chávez et al. (2008) mentioned that a prediction error of 100 Wm^{-2} for H has been reported in some studies. In cases where there is no full cover, some have preferred to use a two-source model whereby the energy balance of soil and that of vegetation are modeled separately (Chávez, et al., 2009b). However, the two-source model is a complex model that requires more input data than the remote sensing-based models discussed in this study.

In the estimation of ET, TABLE 1 shows the discrepancies found in the two methods when compared to ET derived from LAS and ancillary EB sensors.

TABLE 1: COMPARISON OF SEBAL AND METRIC WITH LAS ETHOURLY FOR LAS 1 AND 2 (INDICATED BY ASTERISK)

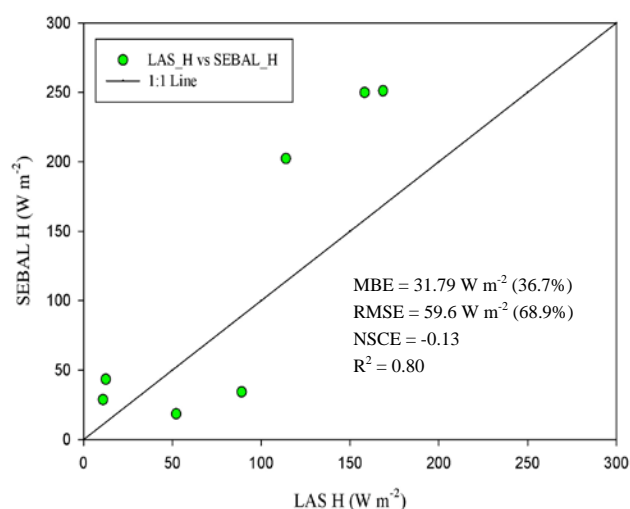| Date	LAS (measured) – mm/h	SEBAL ET mm/h (% error)	METRIC ET mm/h (% error)
07/09/2010	0.775	0.756 (-2.5)	0.762 (-1.7)
08/10/2010	0.747	0.721 (-0.35)	0.707 (-4.0)
08/26/2010	0.352	0.34 (-3.4)	0.347 (-1.4)
09/11/2010	0.679	0.651 (-4.1)	0.698 (2.8)
10/13/2010	0.420	0.577 (15.7)	0.436 (3.8)
09/11/2010*	0.269	0.167 (-37.9)	0.239 (11.1)
10/13/2010*	0.206	0.171 (-17.0)	0.228 (10.7)

*for LAS 2

Figure 2.   Comparing SEBAL-modeled and LAS-measured sensible heat flux (H)
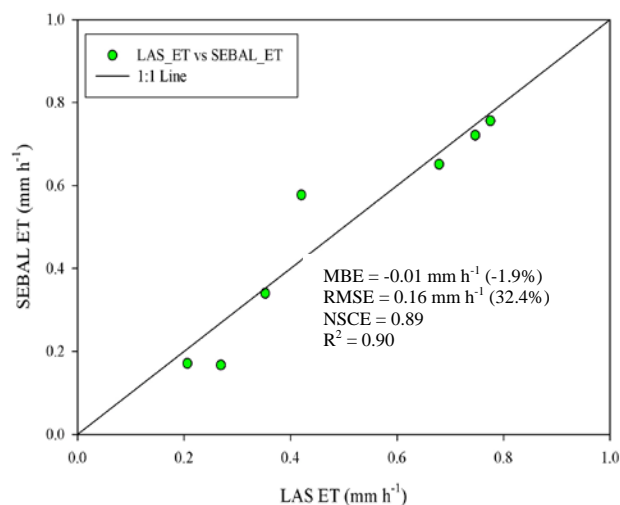

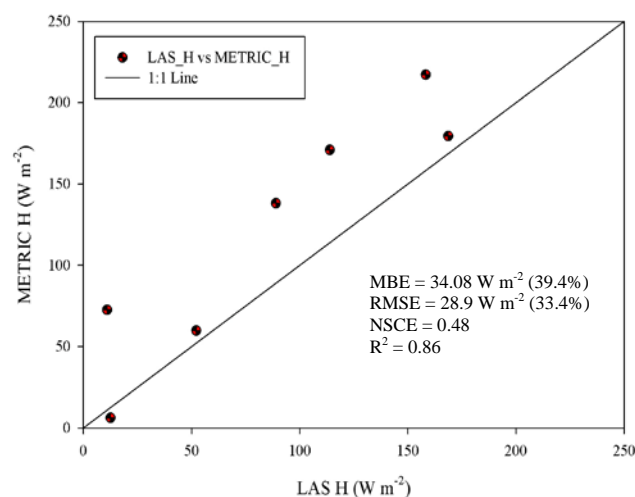Figure 4.   Comparing SEBAL-modeled and LAS-derived hourly ET

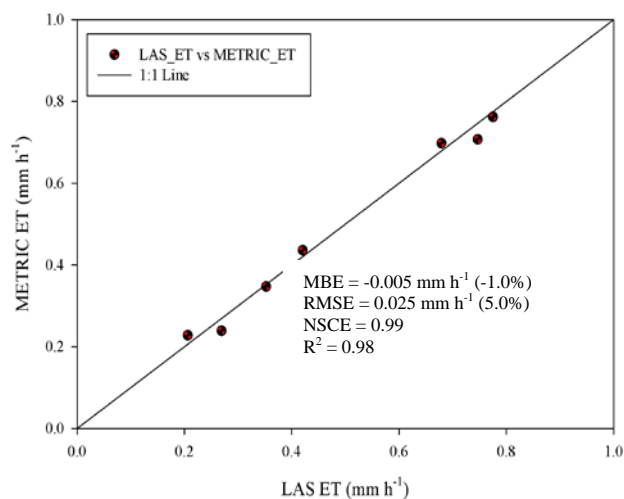Figure 3.   Comparing METRIC-modeled and LAS-measured H

Figure 5.   Comparing METRIC-modeled and LAS-derived hourly ET

TABLE 1 shows that for hourly ET, the percentage error ranged between 0.35-38% for SEBAL, and 1.4–11% for METRIC when compared to the LAS. A negative percentage indicates that the model underestimated while positive means it overestimated ET. Figures 4 and Figure 5 show the graphical comparison of SEBAL and METRIC hourly ET values versus LAS derived values, respectively. SEBAL resulted with a R^2 of 0.90, an MBE of -0.01mm/h (-1.9%) and an RMSE of 0.16 mm/h (32.4%). The NSCE obtained was 0.89 which is an indication of a good model performance.

METRIC results were even better for hourly ET with an R^2 of 0.98, an MBE of -0.005 mm/h (-1.0%), and RMSE of 0.025 mm/h (5%), indicating the model was more accurate. The NSCE was 0.99 which is an optimal value for model performance. METRIC showed more accuracy than SEBAL, and this correlates with the sensible heat flux as determined using the two methods, where METRIC was more accurate than SEBAL (Figures 2 and 3). For both models, the percentage error seemed larger for low ET rates. Chávez et al. (2009b) found comparable results and made a similar observation.

While SEBAL and METRIC seemed not to accurately estimate H when compared to the LAS, the inaccuracy seems to have less effect on the estimation of ET in METRIC than SEBAL. This could be attributed to METRIC's ability to compensate for biases in other components of the energy balance (e.g., R_n and G) and some components of the H calculations, and therefore reduce the error in ET. "The biases inherent in R_n, G and sub-components of H are cancelled by subtraction of a bias-cancelling estimate for H" (Allen et al., 2007). R_n was estimated by the models within an error of 2-12% relative to measured R_n using net radiometers. This was comparable to other studies (e.g., Singh et al., 2008) where predicted R_n had an associated error of about 10%. However the relative error for G ranged from 2% to 60%, with significant error observed at the early stages of growth of the alfalfa or just after harvesting, when the soil is both dry and exposed. However, when calculating LE (as R_n – G – H), SEBAL results in a relative error of 3-52% when compared to LAS derived LE, while METRIC only results in an error of 2-12% which may indicate METRIC's ability to modify H in order to compensate for biases in R_n and especially G.

Also, due to the fact that irrigation of the entire alfalfa field was not done at the same exact time when the lysimeter box was irrigated some heterogeneity in the field, pertaining to surface wetness and biomass development, along the scintillometer path length was expected and therefore the surface conditions may not have been similar with those captured in the satellite remote sensing pixels. This may then contribute to the errors in the remote sensing based H when compared with the LAS measured H.

V. CONCLUSIONS

In this study, SEBAL overall resulted in large errors in the estimation of H. The error may have resulted, to some degree, from the subjective selection of the dry and wet pixels and the assumptions associated with the selection. METRIC seemed to estimate ET more accurately than SEBAL due to the more accurate estimation of H and also due to the allege METRIC's inherent ability to cancel off biases associated with the estimation of other components of the energy balance equation along a crop growing season, therefore resulting in a lower overall error. Both methods incurred larger errors in the

estimation of H for dry field conditions and low biomass presence, especially when there were patches of bare ground in the field. Therefore, there seems to be a research opportunity (need) to consider surface heterogeneity, along with further surface temperature compensation due to atmospheric effects, in the remote sensing-based ET algorithm. The soil heat flux model also should be improved in order to be applicable to a wide range of surface conditions of vegetation covers. In addition, for sparse and heterogeneous surface conditions, the two-source energy balance method, which models the soil and vegetation separately, could be employed in future studies to verify its usefulness and accuracy in determining each term of the energy balance with emphasis on H and ET.

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